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# Designing a Total Productive Maintenance (TPM) Management Model Using a Hybrid Method of Artificial Neural Networks and Hierarchical Clustering in Power Distribution Companies of Northwestern Iran

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**Abstract**

The aim of this research is to design a Total Productive Maintenance (TPM) management model using a hybrid method of artificial neural networks and hierarchical clustering in power distribution companies of northwestern Iran. This study is conducted in power distribution companies of northwestern Iran, which were selected as pilot companies. Determining the optimal maintenance strategy and selecting the best management model for maintenance is of great importance. The findings of this study will be provided to Tavanir and the Ministry of Energy for further implementation in other subsidiary companies. In terms of location, the quantitative data pertains to operational data of the power distribution companies in northwestern Iran. The statistical population includes experts and personnel from the maintenance, repair, and warehousing departments of these companies. The temporal data pertains to operational data from the inventory, accounting, and process systems of power distribution companies in northwestern Iran, spanning from 2017 to 2022. The results of this research indicate that initiating the Total Productive Maintenance process requires strong managerial leadership. Subsequently, processes should be improved and undergo initial feedback evaluations. By considering the strength of human resources and enhancing employee skills, the quality of work processes will be analyzed. As these factors evolve, the system will undergo precise organization and planning. Comprehensive preventive maintenance will ensure workplace safety and health are prioritized. Another aspect that management must address is the advancement of technology and the expansion of automation systems, especially in the implementation of equipment and inventory management subsystems and resource and contract management, which are key priorities of the model. Finally, management must focus on adopting preventive maintenance, self-controlled maintenance, and re-evaluating current practices. Employees should be engaged in achieving these three goals.

***Keywords:*** *hierarchical clustering, power distribution companies of northern Iran, artificial neural networks, Total Productive Maintenance (TPM) management*

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## 1. Introduction

Total Productive Maintenance (TPM) is a systematic approach aimed at optimizing equipment performance through proactive and preventive maintenance strategies, thereby ensuring maximum efficiency and productivity across various industrial sectors. TPM plays a critical role in not only maintaining machinery and equipment but also in enhancing the overall operational performance of organizations. This approach integrates maintenance functions into the manufacturing process, focusing on maximizing equipment effectiveness, improving maintenance processes, and engaging all employees in the maintenance activities. TPM's ultimate goal is to achieve zero defects, zero breakdowns, and zero accidents, contributing to both operational and safety improvements in an organization [1-4].

The TPM concept originated in Japan, particularly within the automotive sector, but has since gained worldwide recognition due to its ability to enhance manufacturing performance [5]. According to Bakri et al. (2013), TPM is seen as either a complementary initiative or a competing one with other quality improvement methodologies such as Total Quality Management (TQM) or Six Sigma [3, 4]. In practice, TPM emphasizes a holistic approach that involves all employees from the top management to shop floor operators, ensuring the system's effectiveness in fostering a culture of continuous improvement [6]. This holistic engagement contributes significantly to enhancing equipment availability, reducing maintenance costs, and increasing productivity in various industries, from manufacturing to service sectors [7].

TPM, as an evolution of preventive maintenance, was developed to address the need for more integrated maintenance systems in industries where equipment breakdowns and inefficiencies resulted in significant losses. The eight pillars of TPM—focused improvement, autonomous maintenance, planned maintenance, quality maintenance, early equipment management, education and training, safety, and administrative TPM—create a comprehensive framework for ensuring equipment reliability [8]. These pillars have been identified as fundamental elements for successfully implementing TPM and achieving operational excellence [9]. Each pillar contributes uniquely to reducing downtime, improving productivity, and fostering a culture of accountability and teamwork among employees [10].

Research has shown that the success of TPM implementation largely depends on the commitment and participation of all employees, from management to operational staff [2]. The integration of TPM into the organizational culture is a key factor in its sustainability, as it requires continuous learning, problem-solving, and improvement [11]. Furthermore, effective leadership and strategic alignment of TPM with organizational goals have been identified as critical success factors [12]. In their study, Kalpande and Toke (2022) emphasized that without strong leadership, the potential benefits of TPM, such as increased equipment availability and reduced maintenance costs, may not be fully realized [13].

Numerous studies have demonstrated that the implementation of TPM can significantly improve manufacturing performance. TPM helps reduce equipment failures, increase Overall Equipment Effectiveness (OEE), and improve productivity in manufacturing environments [14, 15]. For instance, in the automotive industry, TPM has been shown to improve key performance metrics, such as machine uptime, production output, and product quality [16]. Furthermore, TPM contributes to the reduction of production losses by minimizing the six big losses: breakdowns, setup and adjustment, small stops, reduced speed, process defects, and reduced yield [17]. This is achieved by applying a structured approach to equipment maintenance, thereby enabling organizations to improve their production efficiency and reduce operating costs [18].

One of the critical aspects of TPM is its focus on preventive maintenance, which helps avoid unscheduled downtimes and equipment failures that could disrupt production [19]. In a case study of the footwear industry, Reyes et al. (2018) highlighted how TPM implementation led to improved equipment reliability and reduced operational disruptions, thereby enhancing overall productivity [19]. Similarly, the integration of TPM with lean manufacturing principles has been shown to enhance equipment efficiency and manufacturing sustainability [20].

Despite the well-documented benefits of TPM, its implementation is not without challenges. Attri et al. (2013) identified several barriers to TPM implementation, including resistance to change, lack of management commitment, and insufficient training [21]. These barriers can significantly hinder the successful implementation of TPM in an organization, leading to suboptimal outcomes. For instance, the resistance of employees to adopt new maintenance practices can slow down the TPM implementation process, while a lack of management support can prevent the allocation of necessary resources for TPM activities [22]. Additionally, organizations may face challenges in integrating TPM with existing maintenance strategies, particularly in industries with complex manufacturing processes [23, 24].

Another significant challenge in TPM implementation is the technological complexity of modern manufacturing systems. In their study, Lazim et al. (2013) explored how the complexity of production processes can influence the effectiveness of TPM implementation. They concluded that technical complexity requires more sophisticated maintenance strategies and better coordination between different departments [24]. Similarly, the adoption of advanced Industry 4.0 technologies presents new challenges and opportunities for TPM [25]. While Industry 4.0 technologies, such as the Internet of Things (IoT) and big data analytics, can enhance TPM practices by providing real-time monitoring and predictive maintenance capabilities, they also require significant investment in technology and employee training [20].

As industries worldwide continue to adopt more sustainable manufacturing practices, the role of TPM in supporting environmental sustainability has become more prominent [26]. Sustainable TPM (STPM) integrates environmental considerations into maintenance practices, focusing on reducing waste, energy consumption, and emissions [27]. The incorporation of STPM into organizational practices not only improves equipment reliability and operational efficiency but also aligns with global sustainability goals [14]. For instance, Au-Yong et al. (2021) discussed how TPM could be applied in green office buildings to enhance energy efficiency and reduce operational costs [28].

The future of TPM is likely to be shaped by technological advancements and the increasing importance of sustainability. The integration of TPM with emerging technologies, such as artificial intelligence, machine learning, and IoT, will enable more predictive and automated maintenance processes, further enhancing the efficiency and effectiveness of TPM [25]. Additionally, the increasing focus on sustainability will drive organizations to adopt more environmentally friendly maintenance practices, with TPM playing a crucial role in reducing resource consumption and minimizing environmental impacts [27]. However, the successful implementation of TPM requires strong leadership, employee engagement, and the integration of modern technologies to overcome challenges and barriers [2]. As industries continue to evolve, the future of TPM will be shaped by technological advancements and the growing emphasis on sustainability. By embracing these trends, organizations can further enhance the effectiveness of TPM and contribute to a more sustainable and efficient manufacturing environment. The aim of this research is to design a Total Productive Maintenance (TPM) management model using a hybrid method of artificial neural networks and hierarchical clustering in power distribution companies of northwestern Iran.

## 2. Methodology

The present study employs an exploratory mixed-method approach (qualitative and quantitative), with a combination or integrated method for data collection and is considered developmental in terms of its objectives. The research method in the qualitative part is thematic analysis, and in the quantitative part, it is survey-based. Therefore, the statistical sample was selected in two phases:

This research, relying on the existing literature and interviews with experts, employs a mixed-methods approach. The study will be conducted in two phases. The first phase is qualitative, following grounded theory and systematic review methods to identify factors and criteria and to extract the model. In the second phase, the validation and confirmation of the model components, derived in the first phase, will be carried out using quantitative models. The statistical population consists of a set of individuals, components, and factors that share at least one common characteristic. The statistical population of the present study includes senior, middle, and operational managers, as well as expert maintenance and repair personnel of the power distribution companies in northwestern Iran, amounting to 300 individuals. The research sample in the section assessing the status of the power distribution companies in northwestern Iran concerning the current state of preventive maintenance strategies includes all senior and middle managers and heads of departments in these companies, totaling 117 individuals. In the section identifying maintenance tactics and the components of a productive maintenance management strategy, due to the use of expert evaluation methods, the statistical population consists of 16 maintenance and repair experts and managers from the power distribution companies in northwestern Iran.

Various tools, such as observation, interviews, questionnaires, and documents, are available for data collection. The selection of tools should enable the researcher to defend their choice and validate their research findings. To collect information related to the literature of this study and theoretical discussions, a library research method (books and articles in Persian and English, theses, internet websites, etc.) was used. Through this type of study, secondary data were obtained, which were reviewed by the researcher before the study began. Furthermore, after conducting the research, it was found that there are no standardized questionnaires for evaluating Total Productive Maintenance (TPM) management in the power distribution companies of northwestern Iran. Therefore, the questionnaire used in this study was developed by the researcher and includes 15 criteria, consisting of a total of 62 questions (items), as outlined in Table 1:

**Table 1.** Research Criteria

| No. | Criteria Title | Questionnaire Items | Number of Items |
|---|---|---|---|
| 1 | Awareness | 1-4 | 4 |
| 2 | Acceptance | 5-13 | 9 |
| 3 | Maintenance Management and Leadership | 14-16 | 3 |
| 4 | Organization and Workgroup Formation | 17-19 | 3 |
| 5 | Work Processes | 20-23 | 4 |
| 6 | Equipment and Inventory Management | 24-25 | 2 |
| 7 | Self-Controlled Maintenance | 26-30 | 5 |
| 8 | Planned Preventive Maintenance | 31-35 | 5 |
| 9 | Human Resources and Employee Skills | 36-42 | 7 |
| 10 | Technology and Automation Expansion | 43-46 | 4 |
| 11 | Resource and Contract Management | 47-50 | 4 |
| 12 | Reliability Improvement | 51-53 | 3 |
| 13 | Maintaining Quality in TPM Processes | 54-56 | 3 |
| 14 | Safety and Health Maintenance | 57-58 | 2 |
| 15 | TPM Feedback and Results | 59-62 | 4 |

Typically, two types of validity are considered: face validity and content validity. Both face and content validity are forms of validity that are usually assessed qualitatively. If the respondents believe that the questionnaire accurately measures the intended characteristic, the survey has achieved face validity. In this research, the questionnaire was validated by obtaining feedback from experts, professors, and thought leaders.

Reliability or dependability is another technical feature of measurement tools and is primarily concerned with how accurately the tool measures the intended phenomenon or trait. When using a Likert scale to measure different aspects of a complex concept, the researcher can use Cronbach's alpha to assess the reliability. Cronbach’s alpha is an index for measuring internal consistency. This index calculates the average correlation between the items in a survey tool and is used to measure the reliability of the questionnaire. Therefore, Cronbach’s alpha is an indicator of reliability, which is related to the variance of the true score of the "intended construct." In this study, Cronbach’s alpha was used to estimate the reliability of the questionnaire. If the Cronbach’s alpha value exceeds 0.7, the reliability of the questions is acceptable. The Cronbach’s alpha values were above 0.7, confirming the questionnaire's reliability and consistency of the items.

Descriptive analysis involves comparing phenomena from a statistical perspective to describe them, providing valuable information about the nature of the group under study. The statistical indicators used are the same as those employed in descriptive statistics. Data analysis is a multi-step process in which data collected through information-gathering tools are summarized, coded, classified, and ultimately processed. It should be noted that this analysis was carried out using software such as SPSS 26, Lisrel 8.8, Mathworks Matlab R2021B, and Micmac 6.

In extracting and computing the variables used in this research, exploratory factor analysis techniques and expert opinions were employed. To this end, interviews with specialists and reviews of previous studies were conducted before drafting the research. The result of this process was a questionnaire with 62 items based on 15 dimensions, which was accepted and validated by respected professors. Subsequently, the obtained data were subjected to preliminary analysis, one of which was confirmatory factor analysis. The results of this analysis demonstrated the accuracy and precision of the selected characteristics for each dimension.

## 3. Findings and Results

In this section, we examine the characteristics of each of the studied variables in terms of descriptive statistics, as shown in Table 2:

**Table 2.** Descriptive Statistics Results for Each Dimension

| Examined Factors | Mean | Median | Variance | Min | Max | N (Degrees of Freedom) | Kolmogorov-Smirnov Statistic | Significance Level |
|---|---|---|---|---|---|---|---|---|
| Awareness (shenakht) | 2.22 | 2 | 0.899 | 1 | 5 | 116 | 0.172 | 0.194 |
| Acceptance (paziresh) | 2.10 | 2.11 | 0.306 | 1 | 3.56 | 116 | 0.168 | 0.200 |
| Maintenance Management and Leadership (Mrnegahdari) | 1.66 | 1.65 | 0.395 | 1 | 4 | 116 | 0.152 | 0.251 |
| Organization and Workgroup Formation (SazemandehiT) | 1.60 | 1.33 | 0.358 | 1 | 3.33 | 116 | 0.199 | 0.319 |
| Work Processes (Fkari) | 1.60 | 1.50 | 0.308 | 1 | 3 | 116 | 0.196 | 0.233 |
| Equipment and Inventory Management (Mtanbar) | 1.43 | 1.50 | 0.327 | 1 | 3 | 116 | 0.275 | 0.391 |
| Self-Controlled Maintenance (Ntkontorol) | 1.61 | 1.60 | 0.241 | 1 | 3.20 | 116 | 0.128 | 0.220 |
| Planned Preventive Maintenance (Tpbarnameh) | 1.69 | 1.60 | 0.285 | 1 | 3 | 116 | 0.124 | 0.384 |
| Human Resources and Employee Skills (MensaniMk) | 1.73 | 1.57 | 0.314 | 1 | 3.43 | 116 | 0.163 | 0.258 |
| Technology and Automation Expansion (FGSoutomasi) | 2.20 | 2.25 | 0.525 | 1 | 5 | 116 | 0.108 | 0.341 |
| Resource and Contract Management (Mmgarar) | 2.21 | 2.25 | 0.468 | 1 | 5 | 116 | 0.110 | 0.243 |
| Reliability Improvement (Bgetminan) | 1.76 | 1.66 | 0.381 | 1 | 3.33 | 116 | 0.147 | 0.209 |
| Maintaining Quality in TPM Processes (HefzeKR) | 1.75 | 1.66 | 0.514 | 1 | 4.33 | 116 | 0.154 | 0.197 |
| Safety and Health Maintenance (HefzeES) | 1.59 | 1.50 | 0.290 | 1 | 3.50 | 116 | 0.191 | 0.204 |
| TPM Feedback and Results (Bazkhord) | 1.60 | 1.50 | 0.323 | 1 | 3.25 | 116 | 0.211 | 0.177 |

From the data above, we can conclude that the obtained means fully validate the characteristics of each variable. For instance, the mean of the factor "resource and contract management" shows that most data are dispersed around this point. Additionally, the variance values for the studied groups indicate that all of them are greater than zero, supporting the reliability of the factor calculations. Moreover, the minimum and maximum values, such as those for the factors, show that all measurements and data fall within the range of 1 to 5.

A) Training, Learning, and Parameter Determination in Artificial Neural Networks

The use of artificial neural network models can be adapted through the adjustment of network weights and learning type. Therefore, neural networks can quickly adapt to changes in real data. A neural network does not assume any probability distribution or uniformity of data dispersion. Additionally, there are no significant restrictions on input and output functions, and learning algorithms are independent of the number of inputs.

The advantage of using neural networks is that they do not require an initial analysis of the problem or system structure. Thus, neural network models are more robust and flexible compared to conventional statistical methods. In line with the research plan, we will rank the parameters of each dimension in the Total Productive Maintenance (TPM) management model using artificial neural networks. For this purpose, and to assess the performance of the neural network, the data must be randomly divided into two separate groups: a training set and a test set. To train a neural network effectively, the sample used for learning should be representative of the entire population under study. In this research, a random sample of 50 applicants is used for network training and learning.

To ensure effective learning, alongside a good learning sample, it is essential to decide on the neural network structure and the number of neurons in the input, output, and hidden layers. The number of neurons in the input layer corresponds to the number of variables in the dataset that make up the network's inputs. Given the study's goal of classifying applicants into two groups, one neuron is used in the output layer, and one neuron is placed in the hidden layer of the neural network. The results of the neural network training are shown in Figure 1, demonstrating a low error rate for the neural network model.

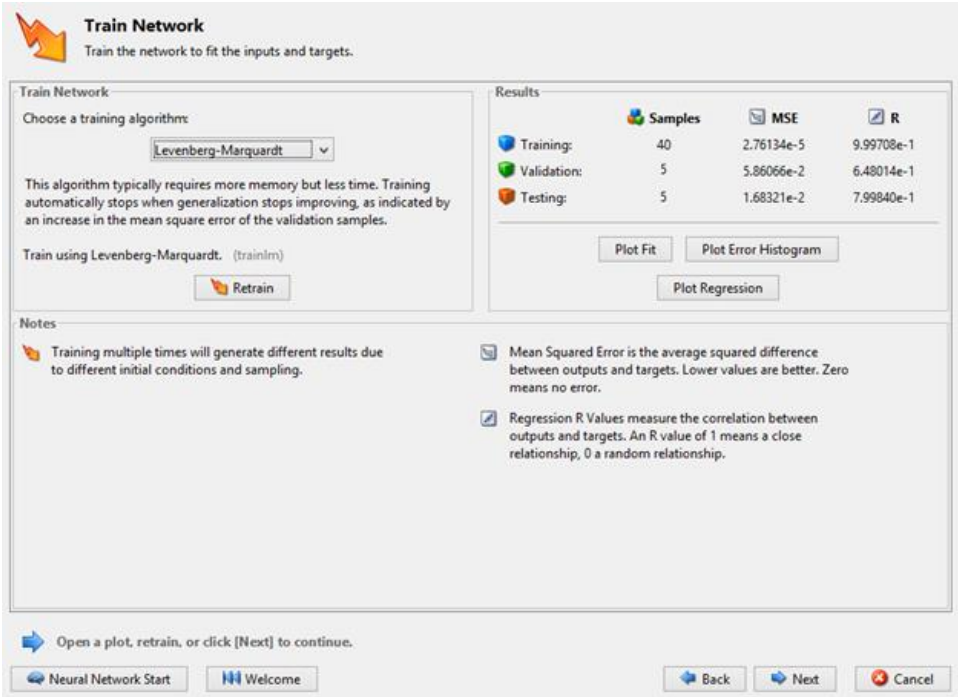


**Figure 1.** Neural Network Learning Panel

The results from the inputs and outputs of the neural network during the training phase in Figure 1 show that 80% of the data (40 samples) were used for training, while the remaining 10% of the observations were used for network evaluation. It is also worth noting that these percentages were obtained after numerous network tests to achieve the lowest error. The output of this model shows that the Mean Squared Error (MSE) is low (2.76). Additionally, the regression statistic (R) is very high (0.99), indicating excellent model accuracy. To further verify model accuracy, a regression graph generated by MATLAB software can also be used.

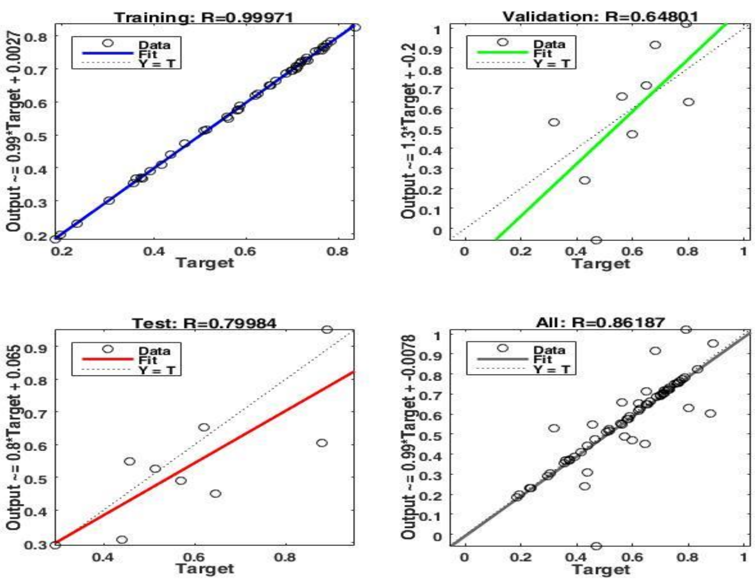

**Figure 2.** Regression Graph

As shown in the graphs above, the most significant value corresponds to the validation graph, with an error of approximately 0.36, indicating the model's proper prediction performance with a small angular deviation from the 100% centerline.

In addition, the network summary is presented below. The top part of Figure 3 displays the network topology, showing the network's input, output, and the number of neurons in the hidden layer (1) and output layer (1). The figure also shows that the data was randomly divided (data division), the network was tested using the Levenberg-Marquardt algorithm, the MSE represents the mean square error, Epoch represents the number of training iterations, and Performance represents the final performance of the neural network, which is 0.52. The Validation Checks represent the optimal network iterations, after which the network's performance no longer improves (2). Figure 4 illustrates this process. The error histogram in Figure 5 shows the number of data points with an error, indicating that approximately 40 observations have an error of 0.013.

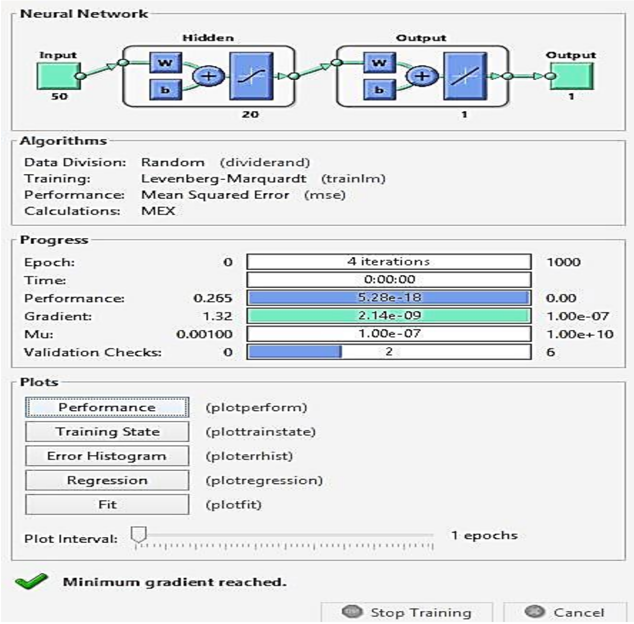


**Figure 3.** Network Topology

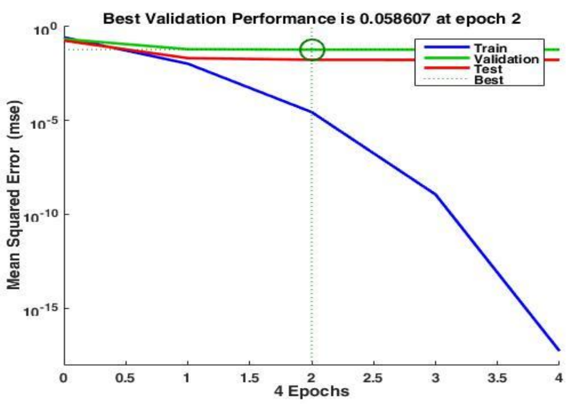


**Figure 4.** Final Optimal Iterations of the Network

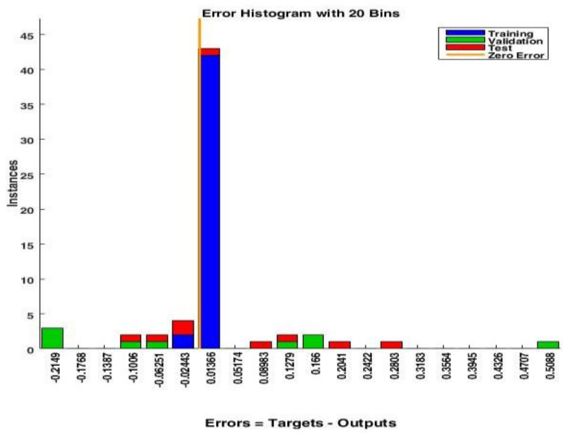


**Figure 5.** Number of Data Points with an Error

B) Ranking the Output Groups in Artificial Neural Networks

Supervised machine learning seeks to optimize a cost function from a series of functions based on the given data. Neural networks receive data, analyze it in hidden layers, and ultimately provide an output. This data can include images, sounds, texts, etc., which must be translated into a machine-readable format. Neural networks are used to classify information; different pieces of information can be grouped based on their similarity to a specific example. As seen from the results of the neural network testing and training in previous sections, the network was trained with 50 observations and is now ready for further analysis. Subsequently, based on the research methodology, data was extracted from 66 tested experts, and the rankings of each dimension were evaluated using the trained neural network. The ranking of the items for each dimension is presented in the following figures:

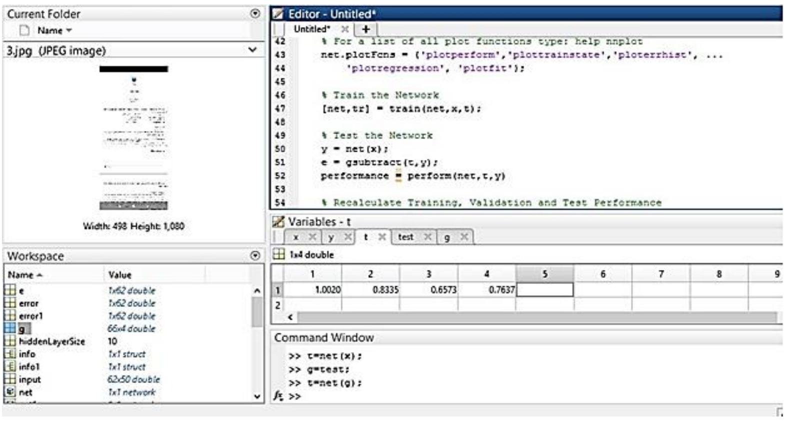

**Figure 6.** Neural Network Ranking for Awareness

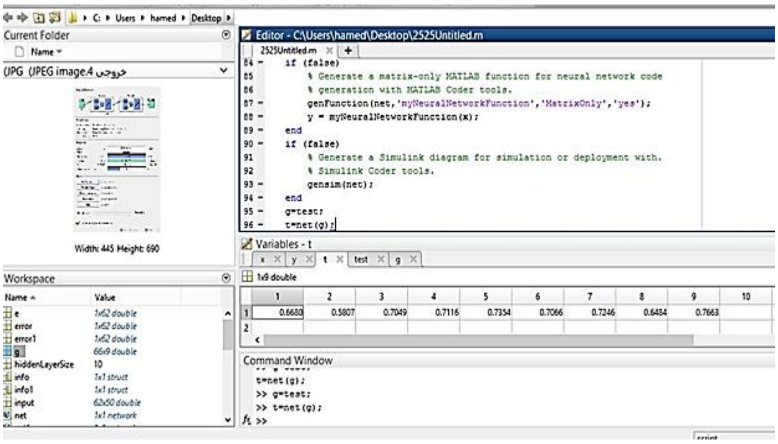


**Figure 7.** Neural Network Ranking for Acceptance

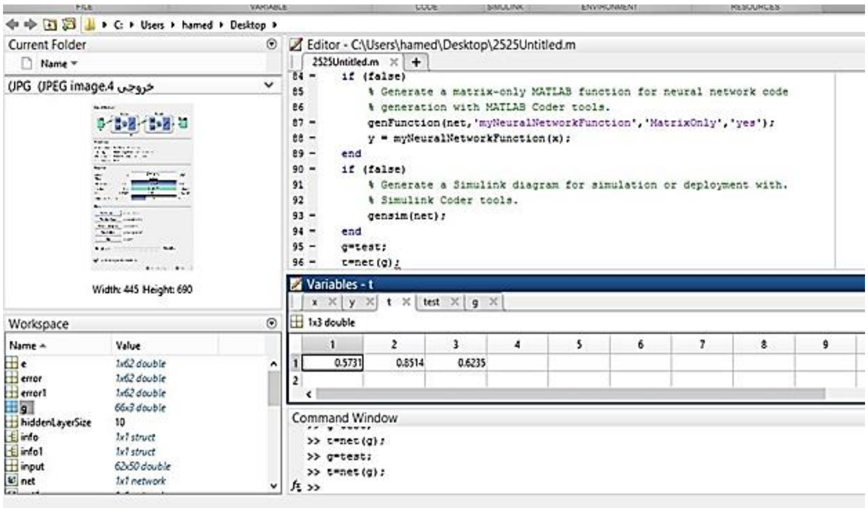


**Figure 8.** Neural Network Ranking for Maintenance Management and Leadership

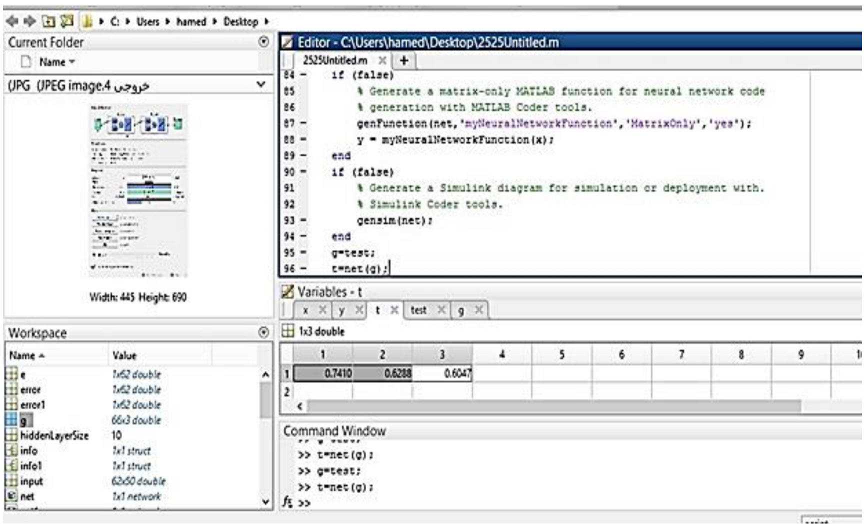

**Figure 9.** Neural Network Ranking for Organization and Workgroup Formation

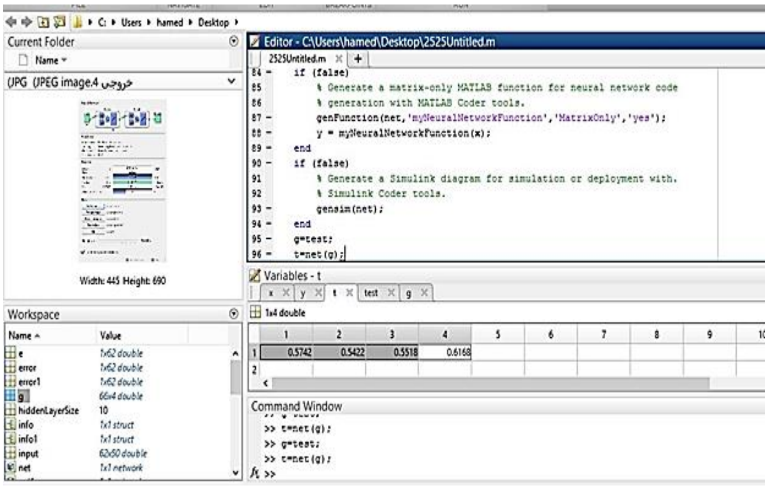


**Figure 10.** Neural Network Ranking for Work Processes

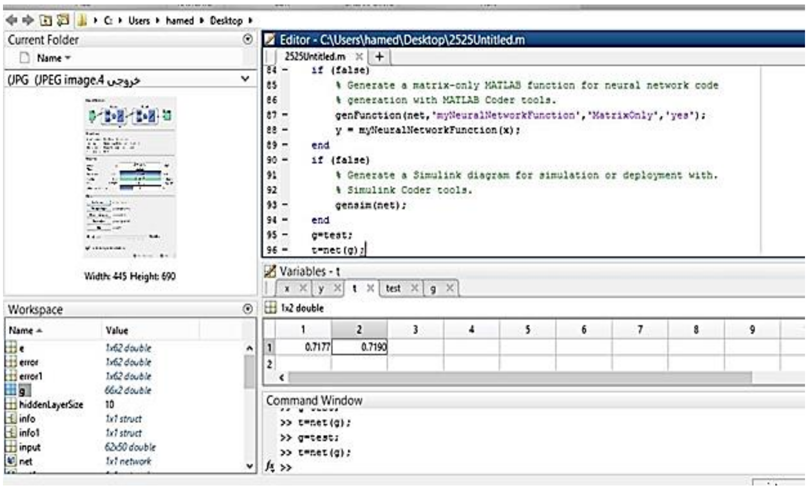


**Figure 11.** Neural Network Ranking for Inventory Management

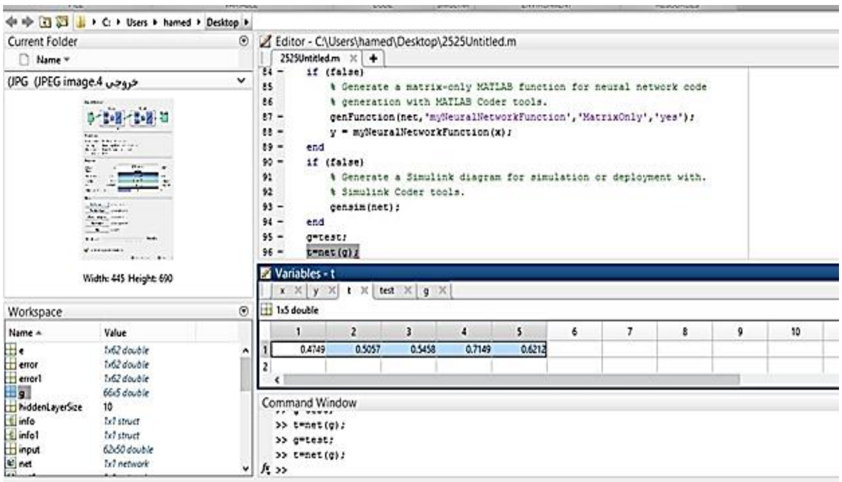


**Figure 12.** Neural Network Ranking for Self-Controlled Maintenance

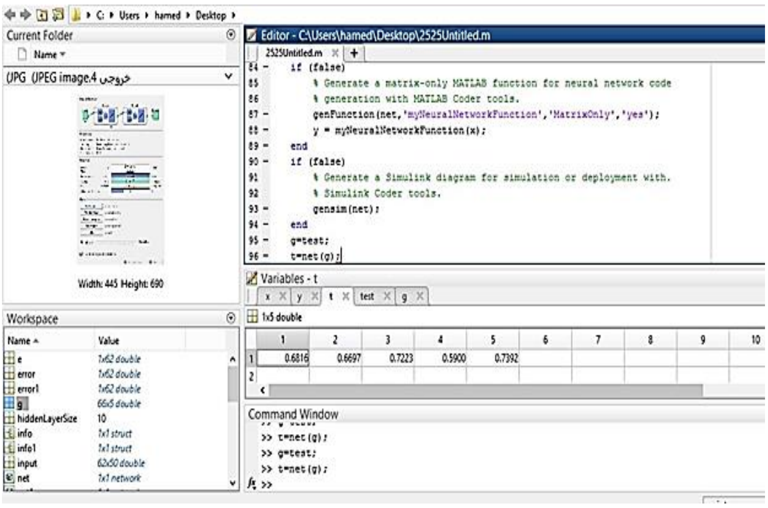


**Figure 13.** Neural Network Ranking for Preventive Maintenance

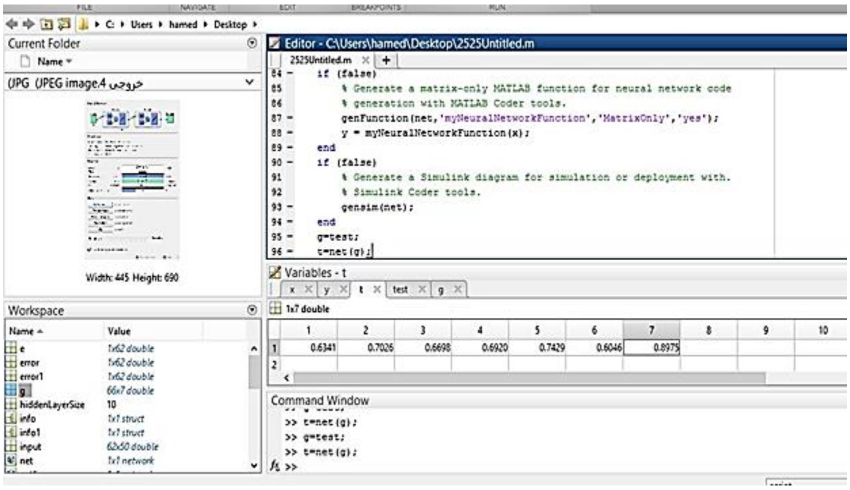


**Figure 14.** Neural Network Ranking for Human Resources and Employee Skills

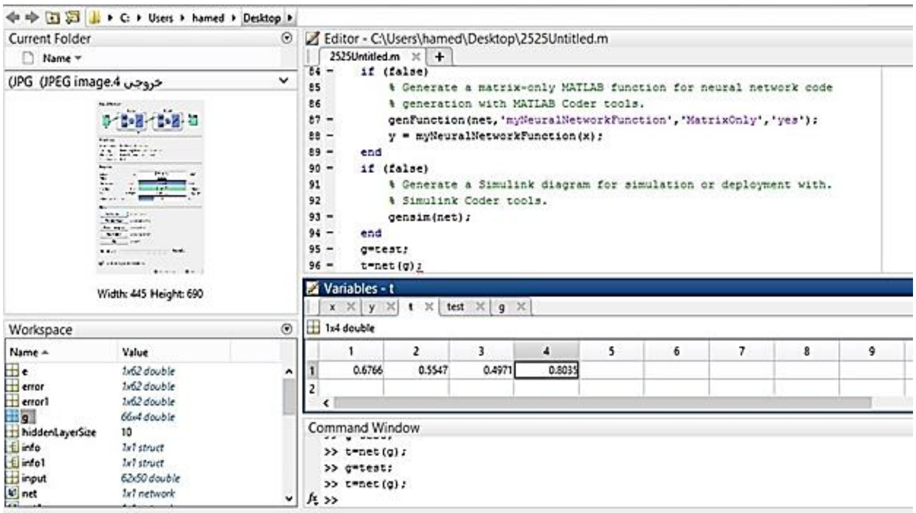


**Figure 15.** Neural Network Ranking for Technology and Automation Expansion

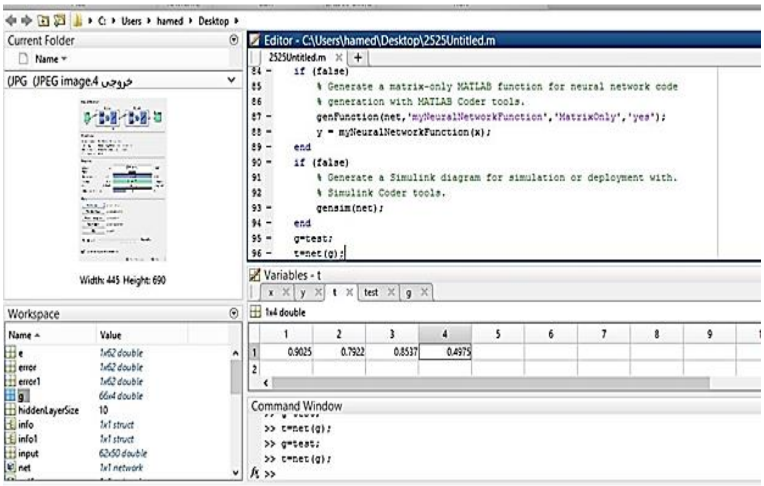


**Figure 16.** Neural Network Ranking for Resource and Contract Management

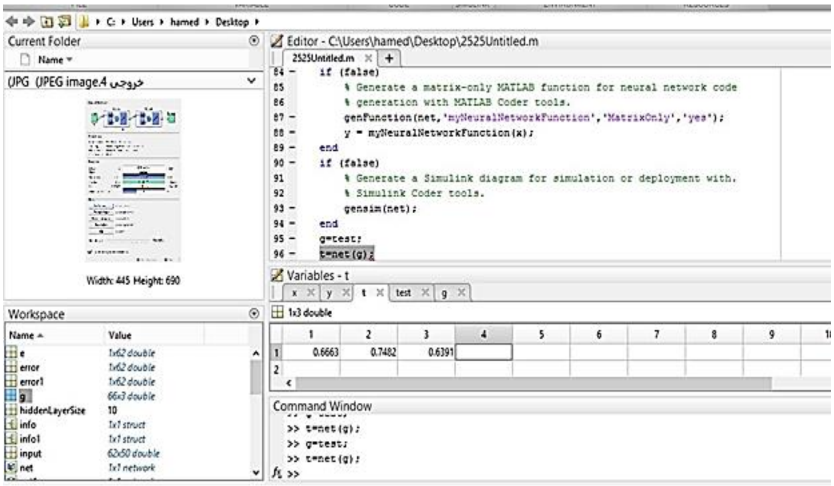


**Figure 17.** Neural Network Ranking for Reliability Improvement

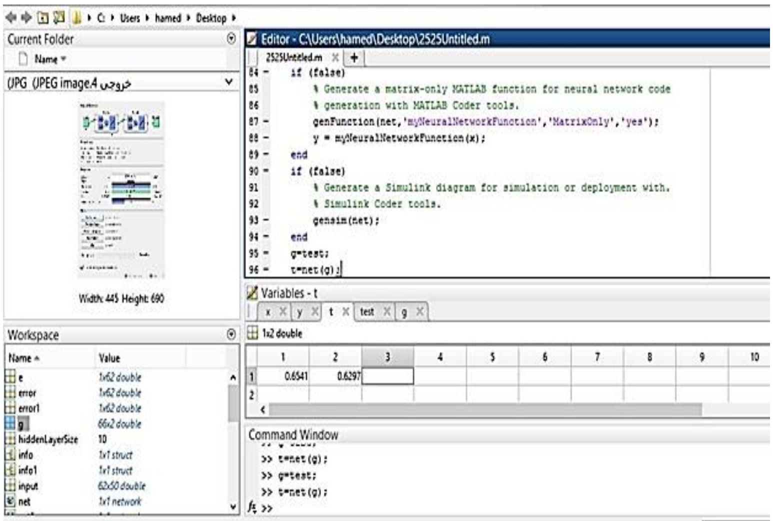


**Figure 18.** Neural Network Ranking for Maintaining Quality in TPM

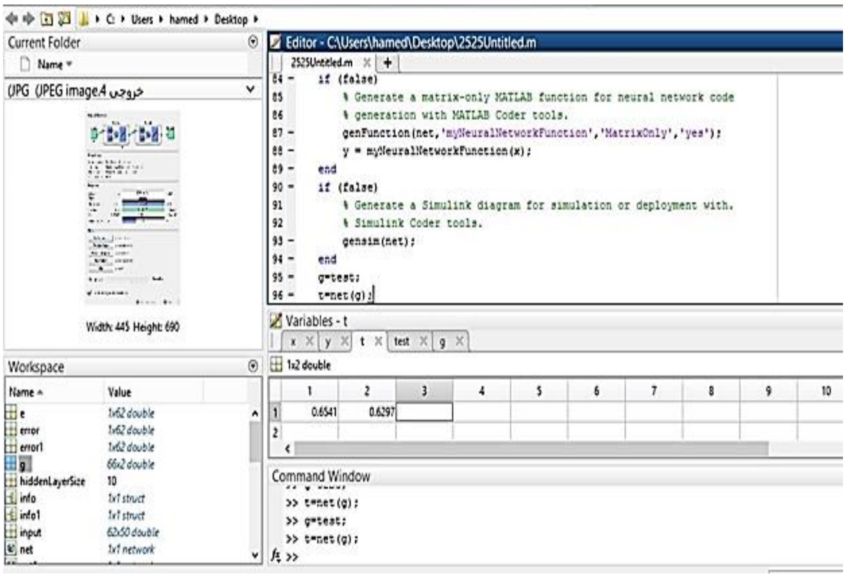


**Figure 19.** Neural Network Ranking for Safety and Health

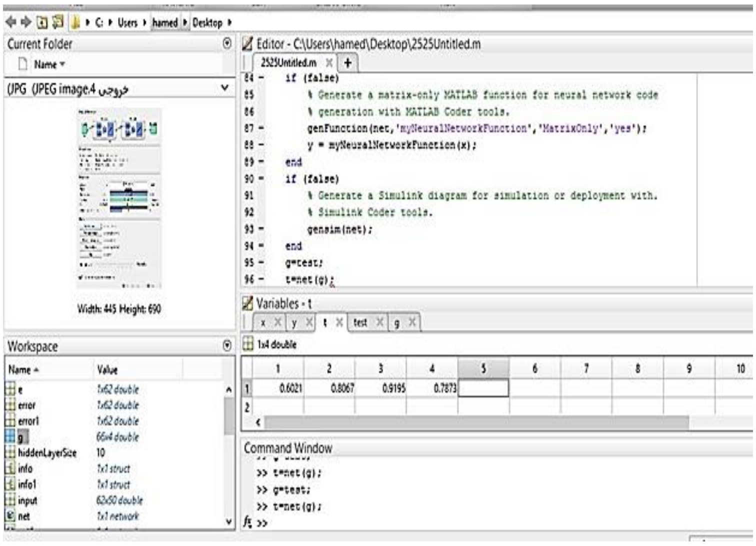


**Figure 20.** Neural Network Ranking for Feedback

C) Initial Clustering of Dimensions Using Hierarchical Clustering Method

One of the machine learning methods known as "unsupervised learning" is clustering analysis. In this method, unlike k-means clustering, each observation may belong to more than one cluster because clusters are formed based on different levels of distance. Therefore, each cluster may be a subset of another cluster at a certain distance level. Clustering is a method that classifies observations into similar groups based on features or attributes.

Choosing appropriate features for clustering is one of the key considerations. Another important aspect is standardizing the data to ensure that the scale of measurement for features does not distort the distance function.

The output of hierarchical clustering is typically shown in the form of a dendrogram. In the hierarchical clustering algorithm, we usually start with the smallest clusters, meaning that initially, each value represents a cluster. Then, the two values with the highest similarity (or smallest distance) are merged to form a new cluster. After this stage, either two values or one value and a cluster, or even two clusters, may merge to create a new cluster.

Among the frameworks in which traditional pattern recognition is formulated, the statistical approach is the most studied, reviewed, and applied in practice. Designing a pattern recognition and statistical pattern identification system involves considerations such as defining pattern classes, environmental assessment, pattern representation, feature extraction and selection, cluster analysis, classifier design and learning, selecting learning and testing samples, and performance evaluation. In this section, based on the results obtained from previous sections, where the observations were ranked and clustered, the most important items are selected and analyzed. This section shows which dimensions, in the most optimal condition, are most efficient and effective for the users, meaning how the desired level of Total Productive Maintenance (TPM) can be achieved in the shortest time with minimal effort. It is noteworthy that to achieve high entropy, selections from items with rankings in different clusters, as shown in Table 3, will be used. This will have a significant impact on pattern formation and model determination in the most effective manner.

**Table 3.** Statistical Results for Dimension Item Selection

| Criterion | Items | Rank | Cluster | Selected Items |
|---|---|---|---|---|
| Awareness | 1. I am somewhat familiar with the Total Productive Maintenance (TPM) system | 1 | 1 | 1 and 2 |
| | 2. I am familiar with the dimensions and processes of the TPM system | 0.83 | 1 | |
| | 3. I have complete knowledge of the Preventive Maintenance (PM) system | 0.65 | 1 | |
| | 4. The TPM system comprehensively involves all organizational dimensions (including management, human resources, finance, safety, quality, individual improvement, and equipment) | 0.76 | 2 | |
| Acceptance | 5. I agree with the creation, expansion, and updating of systems like TPM | 0.66 | 1 | 8, 9, 11, and 13 |
| | 6. The company provides a proper environment for creating and expanding TPM systems | 0.58 | 2 | |
| | 7. Employees in the company are highly inclined towards teamwork | 0.70 | 3 | |
| | 8. The company's senior management fully supports the creation and expansion of quality improvement systems like TPM | 0.71 | 4 | |
| | 9. Similar systems are implemented in the company | 0.73 | 4 | |
| | 10. I agree with a focus on continuous improvement as a core principle of TPM | 0.71 | 1 | |
| | 11. I agree with 5S as a core element of TPM | 0.72 | 1 | |
| | 12. I agree with maintaining quality as a core element of TPM | 0.65 | 1 | |
| | 13. I agree with scheduled preventive maintenance as a core element of TPM | 0.76 | 1 | |

D) Final Research Model

A statistical model is a simplified description or representation of a system or phenomenon we wish to study. A simple model may focus on just one aspect of the system. However, in general, statistical models can be highly detailed, possibly consisting of thousands of variables that are interrelated in complex ways. Therefore, the overall goal is to create models that are sufficiently accurate for our purposes. Based on the aforementioned elements, the final modeling and research framework will be presented.

**Table 4.** Final Dimension Ranking

| Title | No. | Variable | Final Rank |
|---|---|---|---|
| Dimensions | 1 | Maintenance Management and Leadership | 1 |
| | 2 | Reliability Improvement | 2 |
| | 3 | System Feedback and Results | 3 |
| | 4 | Human Resources and Employee Skills | 4 |
| | 5 | Maintaining Quality in Preventive Maintenance | 5 |
| | 6 | Work Processes | 6 |
| | 7 | Organization and Workgroup Formation | 7 |
| | 8 | Scheduled Preventive Maintenance | 8 |
| | 9 | Safety and Health | 9 |
| | 10 | Technology and Automation Expansion | 10 |
| | 11 | Equipment and Inventory Management | 11 |
| | 12 | Resource and Contract Management | 12 |
| | 13 | Acceptance of Preventive Maintenance | 13 |
| | 14 | Self-Controlled Maintenance | 14 |
| | 15 | Awareness | 15 |

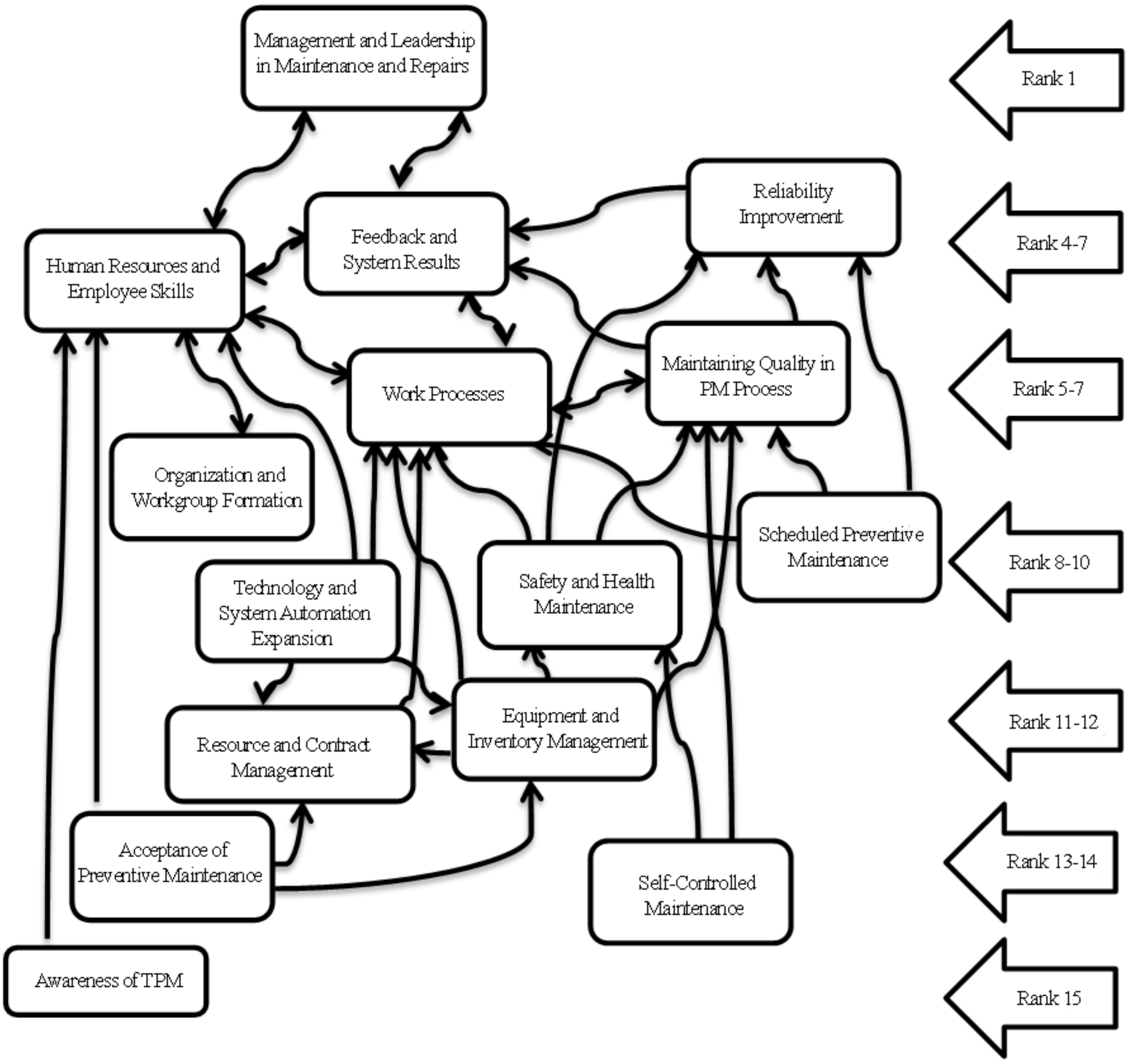


**Figure 21.** Research Model

## 4. Discussion and Conclusion

The present study aimed to investigate the implementation and impact of Total Productive Maintenance (TPM) across various dimensions in power distribution companies of Northwestern Iran. By employing a combination of artificial neural networks and hierarchical clustering techniques, this study identified critical factors that influence the success of TPM implementation, including management and leadership in maintenance, reliability improvement, system feedback and results, and human resources and employee skills. The findings suggest that management and leadership play the most significant role in the success of TPM, consistent with previous research that highlights leadership as a critical enabler in TPM initiatives [12, 13].

The ranking of factors obtained from this study revealed that management and leadership in maintenance received the highest priority in ensuring effective TPM implementation. This result aligns with the work of Hooi and Leong (2017), who found that top-down management support is essential for establishing TPM frameworks, as it drives the necessary changes in organizational culture, resource allocation, and the prioritization of maintenance practices [15]. The study further confirms that effective leadership not only motivates employees but also fosters collaboration between different departments, leading to higher productivity and efficiency in maintenance operations [13]. Similarly, Jain et al. (2018) emphasized that top management involvement is crucial in removing barriers to TPM implementation and ensuring long-term success [29].

Reliability improvement emerged as the second most critical factor influencing the success of TPM, which is consistent with previous research [8, 10]. Reliability improvement is closely associated with reducing machine breakdowns, increasing machine uptime, and enhancing Overall Equipment Effectiveness (OEE) [9]. The focus on reliability in this study reflects the core goal of TPM—minimizing equipment failures through preventive and predictive maintenance strategies [19]. In their study, Reyes et al. (2018) found that improvements in equipment reliability led to significant gains in production efficiency, reduced operational costs, and minimized downtime, all of which are central objectives of TPM initiatives [19].

System feedback and results were ranked third, underscoring the importance of continuous monitoring and feedback loops in maintenance processes. This finding echoes the work of Attri et al. (2013), who highlighted the role of feedback mechanisms in refining maintenance strategies and achieving higher levels of efficiency [21]. By providing actionable insights into the performance of equipment and maintenance activities, feedback systems enable organizations to make informed decisions regarding equipment upgrades, workforce training, and resource allocation [23, 24]. Similarly, Bataineh et al. (2019) found that feedback mechanisms are essential for maintaining a dynamic and responsive TPM system that can adapt to changes in production demands and environmental conditions [10].

Human resources and employee skills were also identified as critical factors in the implementation of TPM. The significance of employee participation in TPM has been well-documented in the literature [2, 19]. In this study, the role of human resources emerged as a vital component, as skilled and motivated employees are essential for performing regular maintenance tasks and identifying potential issues before they escalate [15]. The findings align with Yang and Yang's (2023) bottom-up perspective on TPM, which highlights the importance of engaging employees at all levels to ensure the success of maintenance practices [2]. The development of employee skills through targeted training programs is critical in enhancing their ability to maintain equipment, reduce errors, and contribute to the overall goals of TPM [7]. Moreover, Farihi (2023) found that a well-trained workforce is better equipped to implement autonomous maintenance activities, which is one of the pillars of TPM [6].

The ranking of factors also revealed that maintaining quality in preventive maintenance processes plays a significant role in achieving TPM goals. Quality maintenance ensures that equipment is kept in optimal working condition, preventing defects and reducing variability in production processes [9]. According to Piechnicki et al. (2015), maintaining high-quality standards in preventive maintenance is crucial for minimizing equipment failures and improving product quality [30]. This result is consistent with the findings of Reyes et al. (2018), who observed that focusing on quality maintenance leads to more consistent and reliable production outcomes, thereby enhancing the overall effectiveness of TPM systems [19].

One of the more surprising findings was the relatively lower ranking of technology and automation systems, which is contrary to some recent studies that emphasize the increasing role of Industry 4.0 technologies in enhancing TPM practices [25]. While the integration of automation and digital technologies is seen as a significant enabler for predictive maintenance, the results of this study suggest that in the context of power distribution companies in Northwestern Iran, the traditional aspects of TPM—such as leadership, reliability improvement, and human resources—are still perceived as more critical. This finding may be attributed to the current level of technological adoption within the organization or region, which may not yet fully capitalize on the benefits of automation technologies in maintenance processes [20].

In terms of self-controlled maintenance and acceptance of preventive maintenance, these factors ranked lower than expected, which may indicate that while employees are engaged in maintenance activities, there are still gaps in fully embracing autonomous maintenance practices. This is consistent with the challenges noted by Singh and Ahuja (2014), who found that organizations often struggle with the transition from traditional maintenance methods to self-maintenance systems due to a lack of employee empowerment and insufficient training [31]. However, as noted by Farouq et al. (2023), improving self-maintenance capabilities can lead to significant gains in maintenance effectiveness, as employees become more proactive in identifying and resolving maintenance issues before they lead to major disruptions [32].

Overall, the findings of this study reinforce the importance of a comprehensive, multi-dimensional approach to TPM implementation. By focusing on leadership, reliability improvement, and human resources, organizations can achieve significant improvements in maintenance effectiveness and operational performance [3]. The results also underscore the need for continuous feedback and quality maintenance to ensure the long-term sustainability of TPM initiatives [21]. While technology and automation play an increasingly important role in modern maintenance practices, traditional TPM pillars such as leadership and employee engagement remain critical to the success of maintenance systems in the context of power distribution companies in Northwestern Iran.

This study has several limitations that should be considered when interpreting the findings. First, the study was conducted within the specific context of power distribution companies in Northwestern Iran, which may limit the generalizability of the results to other industries or geographic regions. The unique characteristics of the power distribution sector, including its regulatory environment, operational challenges, and workforce composition, may influence the prioritization of TPM factors. Second, the study relied on a relatively small sample size, particularly in the ranking and clustering analysis. While efforts were made to ensure the representativeness of the sample, the results may not fully capture the diversity of perspectives and experiences within the organization. Lastly, the study's reliance on self-reported data from employees and managers may introduce bias, as respondents may have provided socially desirable answers or overestimated the effectiveness of certain TPM practices.

Future research should explore the implementation of TPM in other sectors and regions to determine whether the prioritization of TPM factors differs across industries. Comparative studies between industries with varying levels of technological adoption, such as manufacturing, healthcare, and services, could provide valuable insights into the role of technology in TPM implementation. Additionally, longitudinal studies could examine the long-term impact of TPM practices on organizational performance, employee engagement, and equipment reliability. Future studies should also consider using larger sample sizes and more objective measures, such as equipment performance data, to complement self-reported data and reduce potential bias.

Organizations seeking to implement TPM should prioritize strong leadership and management support, as these factors are critical for fostering a culture of maintenance and continuous improvement. Management should actively engage employees in the maintenance process, providing training and opportunities for skill development to ensure that staff can effectively contribute to autonomous maintenance activities. It is also essential to establish robust feedback systems that allow for continuous monitoring and improvement of maintenance practices. Lastly, while traditional TPM practices remain important, organizations should explore the integration of Industry 4.0 technologies, such as predictive maintenance and automation, to further enhance the effectiveness and efficiency of their maintenance systems.

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Authors equally contributed to this article.

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## Declaration of Interest

The authors report no conflict of interest.

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## Ethical Considerations

All procedures performed in this study were under the ethical standards.

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